Glaucoma Detection Using Deep Learning and Image Processing

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Abstract - Glaucoma is a progressive eye condition that can silently damage the optic nerve and lead to irreversible blindness if not identified early. Because early symptoms are subtle, effective screening tools are essential. In this study, we present a practical diagnostic framework that integrates classical image enhancement with a lightweight convolutional neural network (CNN) for retinal fundus analysis. The system improves image clarity, isolates the optic disc and cup, and calculates the cup-to-disc ratio (CDR), a clinically recognized marker of glaucoma. A CNN classifier then categorizes images into normal, suspect, or glaucomatous cases. To improve accessibility, a Tkinter-based interface allows users to upload images and view diagnostic outputs in real time. Experimental evaluation demonstrates strong accuracy, sensitivity, and specificity, highlighting the system's potential as a cost-effective solution for early glaucoma screening and clinical support.

Key Words: Glaucoma Detection, Deep Learning, Convolutional Neural Network (CNN), Image Processing, Fundus Imaging, Cup-to-Disc Ratio, GUI-based Diagnosis.

I. INTRODUCTION

Early detection of glaucoma remains a major challenge in ophthalmology, as the disease causes gradual optic nerve damage and often progresses without noticeable symptoms. Globally, over 76 million people are affected, with projections exceeding 110 million by 2040. In India alone, nearly 12 million individuals are estimated to have glaucoma, many of whom remain undiagnosed due to limited screening resources and reliance on subjective clinical evaluation. Traditional diagnosis depends on fundus imaging and optic nerve assessment, which can vary based on clinician expertise and may fail to detect early-stage disease. Recent advances in artificial intelligence, particularly convolutional neural networks (CNNs), enable automated and consistent analysis of retinal images by identifying subtle structural changes. This work presents a hybrid approach combining image processing for optic disc and cup segmentation with deep learning-based classification. The system computes the cup-to-disc ratio and uses a CNN to support glaucoma detection, supported by a Tkinter-based interface for real-time visualization and user interaction.

The main objectives of this study are:

1. To develop a CNN-based classification model for identifying glaucoma from fundus images.
2. To implement image processing techniques for reliable optic disc and cup segmentation and CDR computation.
3. To design a graphical interface that presents both model predictions and extracted clinical features.
4. To assess system performance using accuracy, sensitivity, specificity, and F1-score.

By integrating automated structural analysis with deep learning classification, this study aims to deliver an interpretable, cost-effective, and scalable solution suitable for both clinical settings and remote screening applications.

II. RELATED WORK

Advances in Artificial Intelligence (AI) and Deep Learning (DL) have greatly improved automated glaucoma detection, offering more reliable early diagnosis of this irreversible disease. Most studies emphasize retinal fundus image analysis using Convolutional Neural Networks (CNNs), with growing attention on interpretability to build clinical trust.

Daud et al. [1] provided a comprehensive review of glaucoma detection techniques, highlighting the shift from traditional handcrafted feature extraction to deep learning-based approaches. Their study demonstrated that CNN-based models outperform conventional methods by learning complex visual patterns directly from fundus images, though they noted limited interpretability as a key challenge.

Shyamalee et al. [2] proposed an explainable glaucoma detection framework that integrates visualization techniques such as Grad-CAM to highlight decision-influencing regions in fundus images. Their model achieved high classification accuracy while enabling clinicians to better understand and trust the system's predictions.

Afreen and Aluvalu [3] further explored explainable AI approaches by combining CNN classification with feature visualization to associate highlighted regions with optic nerve head abnormalities. Their results emphasized that interpretability enhances the clinical reliability of automated glaucoma screening systems.

Coan et al. [4] investigated the role of transfer learning in glaucoma detection, demonstrating that pre-trained neural networks can be effectively adapted to medical imaging tasks, particularly when labelled data is limited. They also stressed the importance of dataset diversity to minimize bias across populations and imaging devices.

Rao et al. [5] discussed the integration of AI with traditional glaucoma assessment techniques, such as visual field testing and retinal nerve fibre layer analysis, suggesting that AI can improve efficiency, consistency, and scalability in clinical screening.

Despite these advancements, many existing solutions remain confined to experimental settings without real-time usability. The system proposed in this work addresses this limitation by integrating image processing, CNN-based classification, and an interactive graphical interface, providing immediate visualization of optic disc segmentation, cup-to-disc ratio (CDR), and diagnostic results to support practical clinical use.

III. SYSTEM ARCHITECTURE

The Automated Glaucoma Detection System is designed as a modular framework that integrates image processing, deep learning–based classification, and an interactive graphical interface. The architecture aims to produce clinically interpretable outputs while maintaining scalability and computational efficiency.

To achieve this, the system is organized into five principal layers: the Image Input Layer, Preprocessing Layer, Segmentation and Feature Extraction Layer, Deep Learning Layer, and Visualization Layer. Each module executes a distinct step in the diagnostic pipeline, and the combined workflow is illustrated in Fig. 1.

A. Overall Design

The system is a desktop application that enables users to upload retinal fundus images and receive real-time diagnostic results. Uploaded images are processed through enhancement, optic disc and cup detection, cup-to-disc ratio (CDR) calculation, and CNN-based classification. The architecture is developed using Python 3.10, with OpenCV for image processing, TensorFlow/Keras for deep learning, and Tkinter for the graphical interface. A clear separation between the user interface and backend processing ensures maintainability and supports future enhancements.

The key components of the architecture include:

- Input Module: Supports image formats such as JPEG, PNG, and DICOM.
- Preprocessing Engine: Performs green-channel extraction, denoising, normalization, and contrast improvement.
- Segmentation Engine: Identifies disc and cup boundaries using contour-based and shape-driven operations.
- CDR Computation Module: Computes vertical and area-based CDR values as structural indicators of glaucoma.
- CNN Classifier: Generates class predictions for Normal, Suspect, or Glaucoma.
- Visualization Interface: Displays original images, processed outputs, segmentation overlays, CDR values, and predictions.

The full architectural layout is depicted in Fig. 1.

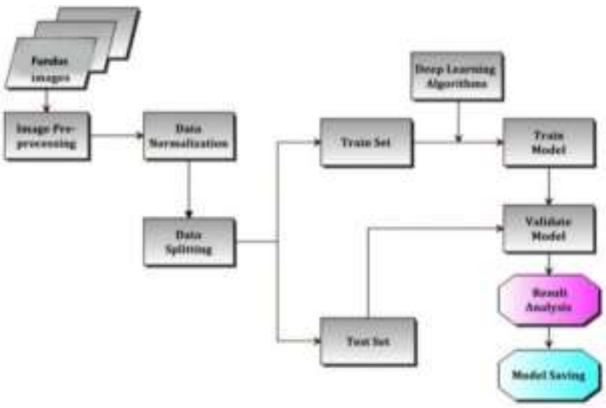

Fig 1: System Architecture

B. Functional Modules

The proposed Automated Glaucoma Detection System is organized into functional modules, each performing a specific task within the diagnostic workflow. Together, these modules enable image preprocessing, feature extraction, glaucoma classification, and result visualization.

- Image Preprocessing Module:
  Enhances fundus image quality by extracting the green channel, reducing noise, improving contrast, and normalizing intensity values to ensure consistent input for further analysis.
- Optic Disc and Cup Segmentation Module:
  Identifies and delineates the optic disc and cup using thresholding, contour detection, and morphological operations. Ellipse fitting is applied to obtain accurate boundaries required for reliable CDR estimation.
- CNN-Based Classification Module:
  Utilizes a trained convolutional neural network to learn structural and textural patterns from fundus images and classify them into Normal or Glaucoma categories using a SoftMax output layer.
- Feature Extraction and CDR Computation Module:
  Computes clinically relevant features such as disc area, cup area, and vertical cup-to-disc ratio (CDR), providing explainable indicators to support the CNN predictions.
- Graphical User Interface (GUI) Module:
  Offers a user-friendly interface for image upload, visualization of preprocessing and segmentation results, display of CDR values, and presentation of final diagnostic outcomes.

C. Workflow Diagram

The workflow begins with image acquisition through the GUI or external datasets. Each image is subjected to preprocessing to correct illumination variation, reduce noise, and enhance structural clarity. The normalized image is then forwarded to the segmentation unit, which extracts disc and cup boundaries using morphological and contour-based approaches.

After segmenting the optic structures, the system computes the CDR and other structural metrics. The enhanced and segmented image is then classified by the CNN into Normal, Suspect, or Glaucoma. The results, including segmentation overlays and CDR, are displayed through the user interface to provide both visual and quantitative insights.

The stepwise data flow is summarized as follows:

1. Image upload through GUI
2. Preprocessing and enhancement
3. Disc–cup segmentation
4. Feature extraction and CDR computation
5. CNN-based classification
6. Visualization of results and diagnostic output

This workflow ensures structured, interpretable, and reproducible decision-making.

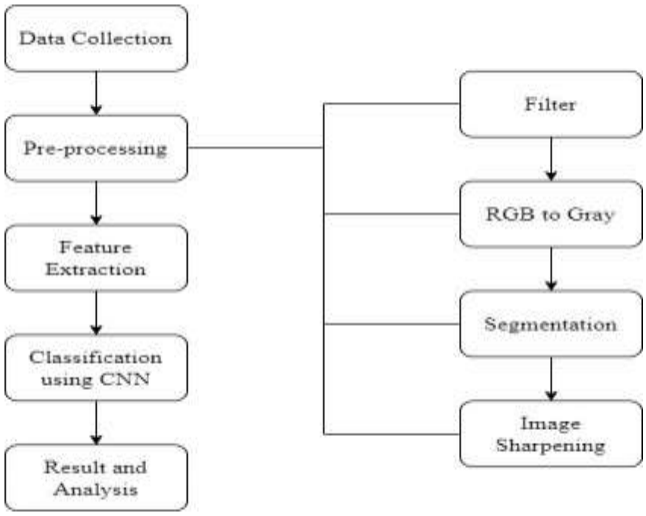

Fig. 2. Workflow diagram of the proposed Glaucoma Detection System.

D. Technology Stack

Component	Technology Used
Programming Language	Python 3.10
Image Processing Libraries	OpenCV, NumPy, Pillow
Deep Learning Framework	TensorFlow with Keras
GUI Framework	Tkinter
Visualization Tools	Matplotlib
Dataset Sources	RIM-ONE, Kaggle GlaucomaDB
Hardware	Intel Core i5 CPU, 8 GB RAM

Component	Technology Used
Model Architecture	Custom CNN (Conv–ReLU–MaxPool–Dense–SoftMax)
Evaluation Metrics	Accuracy, Loss, Sensitivity, Specificity

IV. IMPLEMENTATION

The Automated Glaucoma Detection System is implemented by integrating classical image processing, optic nerve head analysis, deep learning–based classification, and a graphical user interface. The implementation is carried out in four key stages: dataset preparation, image preprocessing and segmentation, CNN-based classification, and GUI integration.

A. Dataset Preparation

Public retinal fundus datasets, including RIM-ONE and Kaggle Glaucoma DB, are used for training and evaluation. Images are resized to 256 × 256 pixels and normalized to a 0–1 range for efficiency. The dataset is divided into:

- Training set: 70%
- Validation set: 20%
- Test set: 10%

To improve generalization and reduce overfitting, basic augmentation techniques are applied, including rotations, horizontal flips, and brightness adjustments.

B. Image Preprocessing

The preprocessing stage enhances the quality of the retinal image and ensures uniformity across the dataset. Using OpenCV, the following operations are performed:

1. Green Channel Extraction – to highlight optic nerve structures
2. Noise Reduction – to reduce noise and smooth uneven illumination.
3. Grayscale Conversion – to simplify subsequent processing
4. Contrast Enhancement – to improve contrast around the optic disc.

These steps produce cleaner and more consistent inputs for the segmentation module.

C. Optic Disc and Cup Segmentation

This stage identifies the optic disc and optic cup, which are essential for structural glaucoma assessment. The segmentation pipeline includes:

- Threshold-based detection of bright circular regions
- Contour extraction for identifying boundaries
- Morphological filtering to refine the shapes
- Ellipse fitting to obtain accurate disc and cup outlines

Following segmentation, the system computes the vertical cup-to-disc ratio (CDR), where higher values indicate a greater risk of glaucomatous damage. The segmented structures and CDR values are displayed through the graphical interface.

D. CNN-Based Classification

A custom CNN model built with TensorFlow/Keras classifies fundus images into Normal, Suspect, or Glaucoma categories. The architecture includes:

- Convolution layers with ReLU activation
- Max-pooling layers
- A flattening layer
- A fully connected dense layer
- A Softmax output layer

The model is trained for 40 epochs using the Adam optimizer with a learning rate of 0.0001. The training and validation accuracy/loss curves (Fig. 4) show stable performance without strong overfitting.

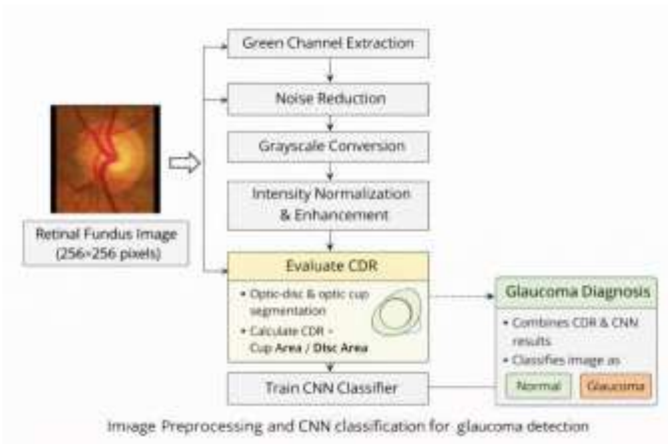

Fig. 3. Image Preprocessing and CNN classification for glaucoma detection

E. Combining Segmentation and CNN Results

For improved reliability, the system considers both structural and learned features:

- CDR measurement from segmentation (clinical evidence)
- CNN prediction from deep learning (AI evidence)

When both indicators suggest glaucoma, the system produces a confident diagnosis. In cases of disagreement, the mismatch is highlighted and the segmentation results are shown for user review. This hybrid strategy improves transparency and trust in the final decision.

F. Graphical User Interface (GUI)

A lightweight GUI developed using Tkinter provides a clear, step-by-step view of the detection pipeline. The interface enables users to:

- Upload retinal images
- View preprocessing results
- Inspect segmented disc and cup boundaries
- Check the computed CDR value
- Run CNN-based classification
- Read the final diagnostic output

The GUI organizes each stage of the pipeline visually, which helps users understand how the system processes an image from start to finish.

G. Performance Evaluation

System performance is assessed using metrics such as accuracy, sensitivity, specificity, and loss. The CNN demonstrates stable training behavior, and the combination of preprocessing, structural analysis, and deep-learning classification offers a dependable approach for screening glaucoma.

V. RESULTS AND DISCUSSION

The proposed Glaucoma Detection System was evaluated to measure classification performance, segmentation accuracy, clinical interpretability, and overall usability. Model performance was assessed using standard metrics including accuracy, precision, recall (sensitivity), F1-score, specificity, and confusion matrix analysis. Training behaviour was further examined through accuracy and loss curves. The results demonstrate that the system offers a reliable and efficient solution for early glaucoma screening.

A. Experimental Setup

All experiments were carried out on a workstation with an Intel Core i5 processor and 8 GB RAM. The system was implemented using TensorFlow/Keras for CNN modeling and OpenCV for preprocessing and segmentation. Retinal fundus images were sourced from the RIM-ONE and Kaggle GlaucomaDB datasets.

For evaluation, 92 unseen images were tested to assess segmentation accuracy, CDR computation, and CNN classification. The model was trained for 40 epochs with data augmentation to reduce overfitting, and results were manually verified against ground truth labels. A Tkinter-based interface validated the complete workflow, ensuring usability and reliability.

B. Evaluation Metrics

Metric	Description	Achieved Value
Test Accuracy	Percentage of correct predictions	92.39%
Precision (Glaucoma/Norma)	Correct positive predictions	0.84 / 0.97
Recall – Sensitivity (Glaucoma/Norma)	Correctly identified glaucoma/normal cases	0.93 / 0.92
F1-Score (Glaucoma/Normal)	Harmonic mean of precision & recall	0.89 / 0.94
Specificity (Glaucoma/Normal)	True negative rate	0.921 / 0.931
Mean Specificity	Average classification reliability	0.9258
Segmentation Reliability	Correct disc & cup localization	High consistency
GUI Usability	User satisfaction with interface clarity	High

TABLE I. System Performance Metrics

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These metrics collectively validate that the system detects glaucoma effectively and maintains balanced performance across all classes.

C. Model Training and Performance Analysis

The CNN training curves shown in Fig. 4 illustrate strong and stable learning behavior.

- The training accuracy increased steadily and reached above 92%.
- The validation accuracy also followed a similar trend, with minor expected fluctuations.
- The training and validation loss curves converged gradually, with final losses of ~0.25 and ~0.35 respectively.

This indicates that the architecture, preprocessing strategy, and hyperparameters are well-tuned for the dataset. No severe overfitting is observed, confirming robust generalization.

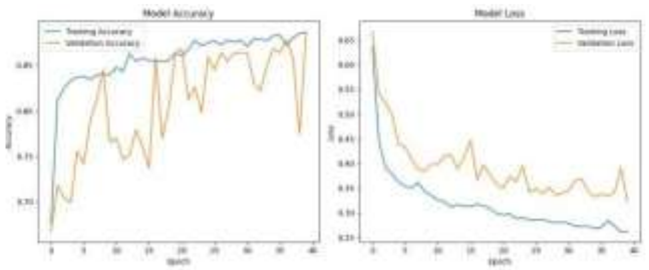

Fig. 4. Training and validation accuracy and loss curves of the proposed glaucoma CNN model.

D. Classification Results and Confusion Matrix Analysis

The classification performance was validated using a confusion matrix and classification report. The results are:

- Accuracy: 92.39%
- Confusion Matrix: [[27 ,2] [5, 58]]
- High recall for glaucoma (0.93) ensures majority of glaucoma cases were captured correctly.
- High precision for normal class (0.97) confirms the model avoids unnecessary false alarms.

These results demonstrate a balanced model, capable of identifying glaucoma with both high sensitivity and high specificity—critical in medical diagnosis.

E. Segmentation and CDR Reliability

The segmentation module successfully detected optic disc and optic cup boundaries across most images. CDR values reflected expected clinical patterns:

- Higher CDR → glaucomatous cases
- Lower CDR → normal cases

This agreement between segmentation measurements and CNN predictions increases the clinical credibility of the system. The clear visualization of segmentation results in the GUI improves interpretability and supports manual validation.

F. System Usability and Interface Evaluation

The Tkinter-based GUI allowed users to upload images, perform preprocessing, view segmentation outputs, and obtain CNN-based diagnosis. Test users found the interface:

- Easy to navigate
- Clear in step-by-step analysis
- Helpful in visualizing disc/cup boundaries
- Responsive even on low-power hardware

This user experience makes the system suitable for academic projects, preliminary screening, and training purposes.

G. Overall System Analysis

The overall system performance indicates that the proposed glaucoma detection model meets its intended objectives with strong reliability and diagnostic consistency. The system demonstrates high accuracy in classifying retinal images, supported by clinically meaningful segmentation and CDR estimation. The lightweight architecture ensures smooth operation without requiring specialized hardware, and the GUI simplifies interaction by presenting each stage—from preprocessing to prediction—in a clear and interpretable format. These outcomes confirm that the model functions not only as an automated classifier but also as a practical screening tool that can aid early detection and support clinical decision-making.

H. Discussion

Compared to conventional rule-based or classical machine-learning approaches, the proposed system provides better adaptability and diagnostic precision through its combination of CNN-based learning and structural CDR analysis. The inclusion of segmentation visualization enhances transparency, allowing users to verify how predictions were generated. The results highlight that this integrated approach can significantly support ophthalmologists and screening programs by improving early detection of glaucoma, reducing diagnostic uncertainty, and promoting a more AI-assisted clinical workflow. With further expansion of the dataset and validation in real clinical environments, the system has the potential to evolve into a dependable diagnostic support tool.

VI. CONCLUSION

This study presents an automated glaucoma detection system that integrates classical image processing with deep learning techniques for early screening. The system performs optic disc and cup segmentation, computes the cup-to-disc ratio (CDR), and applies a CNN-based classifier to generate accurate and interpretable diagnostic results. The inclusion of a graphical user interface enables real-time visualization of each processing stage, improving usability and transparency.

Experimental results demonstrate a test accuracy of 92.39%, along with reliable sensitivity and balanced precision and F1-scores. The consistency between structural CDR analysis and CNN predictions enhances clinical confidence in the system. Overall, the proposed approach offers a cost-effective, scalable, and practical solution suitable for clinical environments, academic use, and remote glaucoma screening applications.

FUTURE SCOPE

Future work may focus on improving robustness by training the system on larger and clinically diverse retinal fundus datasets, enabling better generalization across populations, imaging devices, and glaucoma stages. Incorporating advanced deep learning–based segmentation architectures such as U-Net, Deep Lab, or attention-based networks can further enhance optic disc and optic cup boundary detection, resulting in more accurate cup-to-disc ratio (CDR) computation.

Additionally, integrating complementary clinical biomarkers such as retinal nerve fiber layer (RNFL) thickness, visual field (perimetry) analysis, and retinal vessel density can support a multi-modal glaucoma screening framework. Deploying the system as a web-based or mobile application and conducting large-scale clinical validation with ophthalmologists would further strengthen reliability, regulatory acceptance, and real-world clinical adoption.

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